

FACE RECOGNITION USING EIGEN FACES AND DISCRETE COSINE TRANSFORM APPROACH

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in

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by

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CERTIFICATE

This is to certify that the thesis titled “**Face Recognition using Eigen Faces and Discrete Cosine Transform Approach**” submitted by **Miss Prabartika Sahoo** in partial fulfilment of **Bachelor of Technology in Electronics and Communication Engineering** at **National Institute of Technology, Rourkela** is an authentic work carried out by her under my supervision and guidance.

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DECLARATION

I, hereby declare that the project work entitled “**Face Recognition using Eigen Faces and Discrete Cosine Transform Approach**” is an original work done under **Prof. Sukadev Meher** in **National Institute of Technology, Rourkela**. Every endeavour has been made to acknowledge contributions of others involved with due reference to the literature. This work is being submitted as a part of the partial fulfilment of the requirements for the degree of **Bachelor of Technology in Electronics and Communication Engineering** at National Institute of Technology, Rourkela for the academic session 2010– 2014.

Prabartika Sahoo

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ABSTRACT

Face is a complex, multi-dimensional and meaningful visual stimuli for which it has been extremely difficult to construct a robust model for face recognition. In this thesis, Face Recognition is done by Eigen Faces Approach and by Discrete Cosine Transform (DCT) approach. Face images are projected onto a featured space called 'Face Space' that encodes best variation among known face images. The Face Space is defined by Eigen Face which are Eigen Vectors of the set of faces in the database. The DCT approach exploits the feature extraction capability of the Discrete Cosine Transform invoking both geometric and illumination normalization techniques which increase its robustness to variations in Facial images such as variation in scale, orientation, illumination variation and presence of some details such as dark glasses, beards and moustache etc. These methods were tested on a variety of Face Databases such as The Achermann Database, The Olivetti Database and The MIT Database having different variations and results were also observed.

CONTENTS

Certificate	1
Declaration	2
Acknowledgement	3
Abstract	4
List of Figures	5
Chapter 1	
Introduction	7
1.1 Biometrics	8
1.2 Face Recognition	9
Chapter 2	
Eigen Face Approach	11
2.1 Introduction	12
2.2 Construction	14
Chapter 3	
Discrete Cosine Transform	17
3.1 Introduction	18
3.2 Definition	19
3.3 Basic Algorithm for Face Recognition	21
Chapter 4	
Implementation	23
4.1 Eigen Face Approach	24
4.2 Direct Cosine Transform	26
Chapter 5	
Results	30
5.1 Result of Eigen Face Approach	31
5.2 Results of Direct Cosine Transform	36
Chapter 6	
Conclusion	40
Bibliography	42

List of Figures

1. Figure 1 : Database of Faces
2. Figure 2 : Mean Image
3. Figure 3 : Eigen Faces of faces in Figure 1
4. Figure 4: Flow Chart of Face Recognition Algorithm using DCT
5. Figure 5: Flow Chart of Face Recognition algorithm using Eigen Faces
6. Figure 6: The Achermann Database
7. Figure 7 : The Olivetti Database
8. Figure 8: The MIT Database
9. Figure 9: The CIM database
10. Figure 10: Database of people having various age, gender and skin tone
11. Figure 11: Result of Eigen face approach
12. Figure 12: Result of Eigen face approach for a known face
13. Figure 13: Result of Eigen face approach for an unknown face
14. Figure 14: Result of Eigen face approach for an image, other than a face
15. Figure 15: Result of Eigen face approach for an image, other than face
16. Figure 16: Recognition Accuracy vs No of Training Images per person
17. Recognition Accuracy vs No of DCT coefficients
18. Recognition Accuracy vs Normalised Faces
19. Cumulative Recognition Accuracy as a function of rank for variety of conditions.

Chapter 1

Introduction

1. INTRODUCTION

1.1 BIOMETRICS

Biometrics is the technology which deals with identification or recognition of individual based on their biological or behavioural characteristics such as face, iris, fingerprint, hand, voice, and signatures. It is used in the process of authentication of a person by verifying who he or she claims to be.

Biometrics can be broadly classified into two basic domains, namely Physiological and Behavioural.

Physiological Biometrics is particularly based on measurements and the data which is derived directly from measurement of human body parts. These include:

- Fingerprint Scan
- Hand Scan
- Iris Scan
- Facial Recognition
- Retina Scan

Behavioural Biometrics is based on the data and measurements derived from a particular action of a human being. These include:

- Voice Scan
- Signature Scan
- Keystroke Scan

As the technology of Biometric matures, there will be an increase in interaction among the Biometric market, biometric technology and the identification application. Using this we can verify the identity of a person which has dynamic effects in the security and surveillance

management, protecting the privacy rights of the individuals, more convenient and easier in fraud detection, much better than password or smartcards.

1.2 FACE RECOGNITION

Face is a complex multi-dimensional structure for which it has been extremely difficult to construct detailed neuro-physiological and psycho-physical models for face recognition. In our social life, face plays an important role in identifying a person in our day-to-day life. We remember many faces we meet throughout our life and recognise them at a glance even after so many years. But variation in facial geometry can occur due to ageing and also because of the presence of some details such as beards, glasses and change in our hair styles.

Face recognition is a sub area of Biometrics where basic human traits are matched with the existing datas and depending on the result, identity of a person is traced. Face Recognition Technology analyses the pattern, structure, positioning and shape of different facial attributes. As image processing is largely software based, facial features are extracted and different algorithms are implemented in the software which are efficient and modifications are also done to improve existing models.

With the help of this technology, computers are able to detect and recognise faces, and this can be applied to a variety of day to day applications such as verifying identity, recognising criminals, tagging images on social networking sites. In these technologies, features are first extracted from the face, processed and then compared with the faces stored in the database. If it is a known face, the system may show a similar face existing in the database and if it is unknown, it will not recognise the face.

Objectives of a Robust Face Recognition System

A face recognition system may encounter various types of disturbances during the recognition process because of the dynamic nature of the faces. A robust face recognition system should have the objectives given below:

- **Scale Invariance:** Face images of the same person can be presented to a system at different scales. It happens because of the focal distance between the camera and the face. With the distance getting closer, face image gets bigger.
- **Shift invariance:** Face images of the same person can be presented to a system at different orientations and perspectives. For instance, image of face of the same person can be obtained as profile and frontal views. Even head orientation may also change due to rotations and translation.
- **Illumination invariance:** We can present different images of the face a person to a system by taking images under different conditions of illumination such as, by varying the strength and position of the light source.
- **Emotional expression and detail invariance:** Expressions such as smiling or laughing can also create difference in the face images of a person. Also presence of some details can also create problem such as beards, moustaches or dark glasses.
- **Noise invariance:** A face recognition system which is robust, has to be insensitive to the noise generated by cameras or the frame grabbers. It should even function under images which are partially occluded.

Chapter2

Eigen Face Approach

2. Eigen Face Method

2.1 Introduction

Face recognition has been a subject of a wide spread research for quite a few years and this has led to development of various algorithms. Now let us briefly look at various principles that are used for face recognition. Some of the common methods used for face recognition are the information theory approach, neural network approach, , the multi resolutional approach, the statistical approach - primarily based on histograms , and the eigen face approach. In this project we would be giving emphasis on the Eigen Face Method which was originally suggested by two MIT scholars Matthew A. Turk and Alex P. Pentland in 1991. In this approach, the mean face image is calculated by averaging set of faces in the database. Then difference between the average face and the faces in the database is found out. The linear projection of image is taken on to a low dimensional image space and then the difference is weighed with respect to a set of eigen vectors. The face image is recognized as a known face, if the difference (weight) is below certain threshold, otherwise it is recognized as unknown face, or it is not a face at all. Some of the drawbacks of this approach are illumination, difference in scale, facial expression, the background, head orientation. To solve some of these problems the location of the head can be identified and zoomed until maximum portion of the face is visible. Camera's lighting can also be set based on the time of the day.



Figure 1 : Database of Faces

The above picture shows a set of images being used to create an eigen space needed for a face recognition system. The aim of the project is to apply eigen face method to recognize the face of a person. The overall job is to recognize the identity of a person accurately and carry out further work based on the result of this identification process. Security reason being one of the most important need of face recognition, still it can also be used in various areas such as to quickly retrieve and access various types of records such as medical record, criminal record, etc. It is important to solve this problem because through this, we can allow people to take preventive measures and also provide better services, for example, in case of taking a doctor's appointment, or allowing access of a person to an area which is secure.

2.1 Construction

This section gives instructions to be followed step-by-step along with images and formulas on how to recognize faces and implement this in Matlab.

Steps

1. The first step here is to acquire a training set S with M face images. In our example $M = 25$ as shown in figure 1. Each image is transformed onto a vector of size N and then placed in the set.

$$S = \{ \Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M \}$$

2. After obtaining the set, the mean image (Ψ) is calculated.

$$\Psi = \frac{1}{M} \sum_{n=1}^M \Gamma_n$$



Figure 2 : Mean Image

3. Then the difference Φ between the input image and the mean image is found.

$$\Phi_i = \Gamma_i - \Psi$$

4. Next we had to sought a set of M orthonormal vectors, \mathbf{u}_n which best describes the data distribution. Then the k^{th} vector, \mathbf{u}_k , was chosen such that

$$\lambda_k = \frac{1}{M} \sum_{n=1}^M \left(\mathbf{u}_k^T \Phi_n \right)^2$$

is a maximum, subjected to

$$\mathbf{u}_l^T \mathbf{u}_k = \delta_{lk} = \begin{cases} 1 & \text{if } l = k \\ 0 & \text{otherwise} \end{cases}$$

Note: λ_k and \mathbf{u}_k are the eigen values and eigen vectors of the covariance Matrix \mathbf{C} .

5. \mathbf{C} , the covariance matrix was obtained in this manner :

$$\begin{aligned} \mathbf{C} &= \frac{1}{M} \sum_{n=1}^M \Phi_n \Phi_n^T \\ &= \mathbf{A} \mathbf{A}^T \end{aligned}$$

$$\mathbf{A} = \{ \Phi_1, \Phi_2, \Phi_3, \dots, \Phi_n \}$$

6. \mathbf{A}^T

$$L_{mn} = \Phi_m^T \Phi_n$$

7. Once the eigen vectors, $\mathbf{v}_1, \mathbf{u}_1$ are found,

$$\mathcal{U}_l = \sum_{k=1}^M v_{lk} \Phi_k \quad l = 1, \dots, M$$

The following images are the Eigen Faces of the set of images given as input.

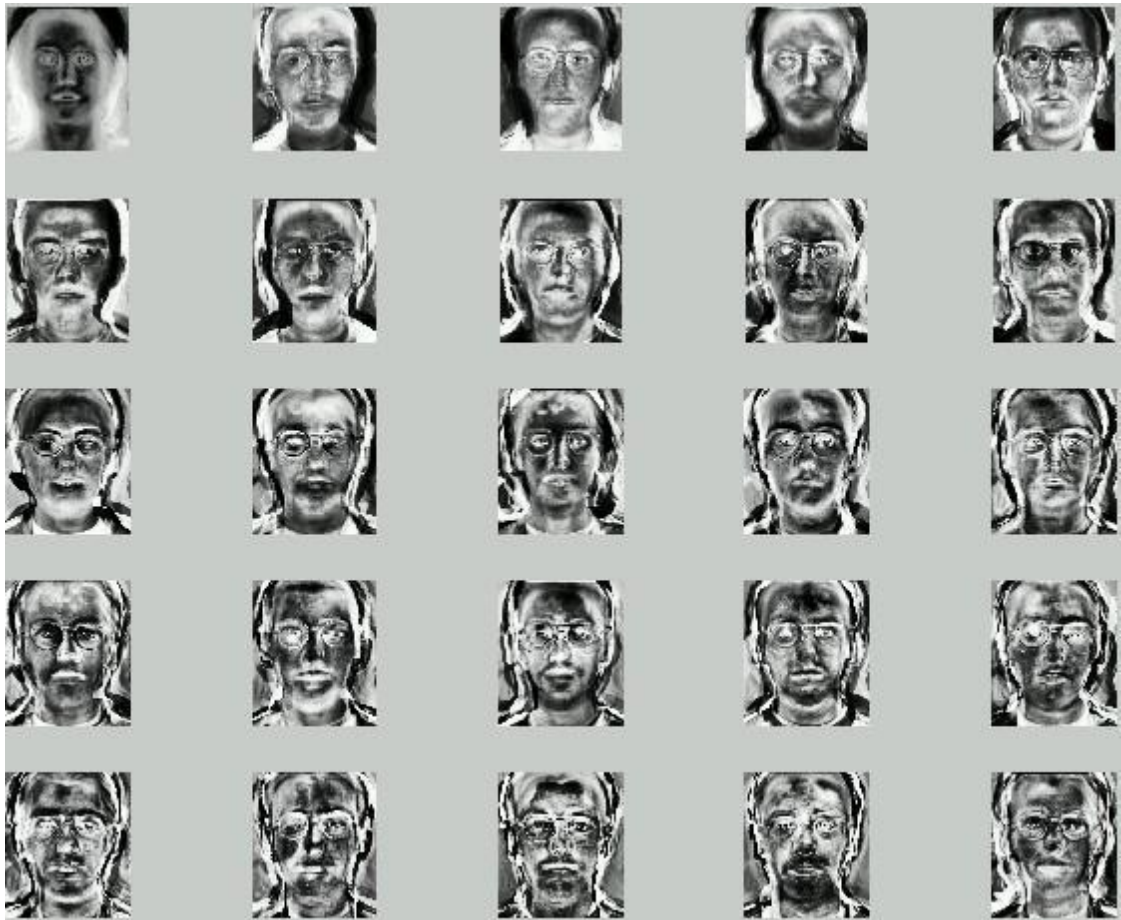


Figure 3 : Eigen Faces of faces in Figure 1

Chapter3

Discrete Cosine Transform (DCT) Approach

3. DISCRETE COSINE METHOD

3.1 Introduction

Every transform is a type of mathematical operation and when it is applied to a signal, being processed converts it to another different domain and it can also be converted back to the original domain by the use of the inverse transform operation. The transform gives us a set of coefficients which acts as feature vectors describing the given signal and helps us to regain the original samples of the input signal. There are some mathematical transforms which can produce decorrelated coefficients such that maximum of the signal energy is concentrated in a less number of coefficients.

The Discrete Cosine Transform (DCT) can be described as a finite sequence of data points which are in terms of summation of cosine functions oscillating at different frequencies. Like other transforms, it also attempts to decorrelate a given signal. After being decorrelated, the transform coefficient are encoded independently in such a way that there is no loss in compression efficiency. The DCT coefficients are reflection of the different frequency components which are present in it. The coefficient at the first place of the DCT refers to the DC component of the signal which is its lowest frequency and most of the time, it carries the maximum of the relevant information present in the input signal. The signal's higher frequencies is represented by the coefficients present at the end and these generally represent the finer details about the original signal. The remaining coefficients carry other levels of information of the input signal given.

3.2 Definition

The Discrete Cosine Transform (DCT) was introduced for the first time by Ahmed, Natarajan and Rao in 1974. Ever since, with the increase in its popularity, till now many other variants have been proposed (Rao and Yip, 1990).

Wang (1984) categorized DCT into four different transformations, which are DCT-I, DCT-II, DCT-III, and DCT-IV. Out of these four classes defined by Wang, DCT-II is used as DCT and DCT-III as its inverse operation.

If we have an input sequence $u(n)$ having length N , its DCT, $v(k)$, can be obtained by the following equation:

$$v(k) = \alpha(k) \sum_{n=0}^{N-1} u(n) \cos \left(\frac{(2n+1)\pi k}{2N} \right)$$

$$0 \leq k \leq N-1$$

where

$$\alpha(0) = \sqrt{\frac{1}{N}}, \alpha(k) = \sqrt{\frac{2}{N}} \quad 1 \leq k \leq N-1$$

Alternatively, the sequence $u(n)$ can be considered as a vector and the Direct Cosine Transform applied to this vector as a transformation matrix in order to find the output $v(k)$.

Here the DCT transformation matrix, $C = \{c(k, n)\}$, can be defined as follows:

$$c(k, n) = \begin{cases} \frac{1}{\sqrt{N}} & k=0, \quad 0 \leq n \leq N-1 \\ \sqrt{\frac{2}{N}} \cos \left(\frac{(2n+1)\pi k}{2N} \right) & 1 \leq k \leq N-1, \\ & 0 \leq n \leq N-1 \end{cases}$$

where n and k are the column and row indices, respectively. Now, the DCT of the sequence $u(n)$ can be written as

$$\mathbf{V} = \mathbf{C}\mathbf{u}$$

The inverse discrete cosine transform operation can be used to obtain $u(n)$ from $v(k)$. It can be written as:

$$u(n) = \sum_{k=0}^{N-1} \alpha(k) v(k) \cos\left(\frac{(2n+1)\pi k}{2N}\right)$$

with the value of $\alpha(k)$ being given previously. Using the above equations, the inverse discrete cosine transform, u , of the output v is calculated by multiplying the inverse of the matrix C to the vector, v . That is, the inverse discrete cosine transform can be calculated from

$$\mathbf{u} = \mathbf{C}^{-1}\mathbf{v}$$

From these definitions, it is observed that when the discrete cosine transform is applied to a given sequence, it is decomposed into its weighted sum of basis cosine sequences. It is well known from the above equation that $u(n)$ can be reconstructed by the sum of cosine terms which are weighted by the coefficients of DCT obtained earlier. The basis sequences of DCT are nothing, but the rows in the matrix C .

3.3. Basic Algorithm face recognition

This face recognition algorithm using DCT, which is used in this paper is depicted in Fig. 2. It has face normalization and recognition also. Here the system gets an image as input containing a face along with the coordinates of the eye. Then execution of both geometric and illumination normalization functions is done. Once a normalized (and cropped) face is obtained, it is then compared with other faces in the training set, under the

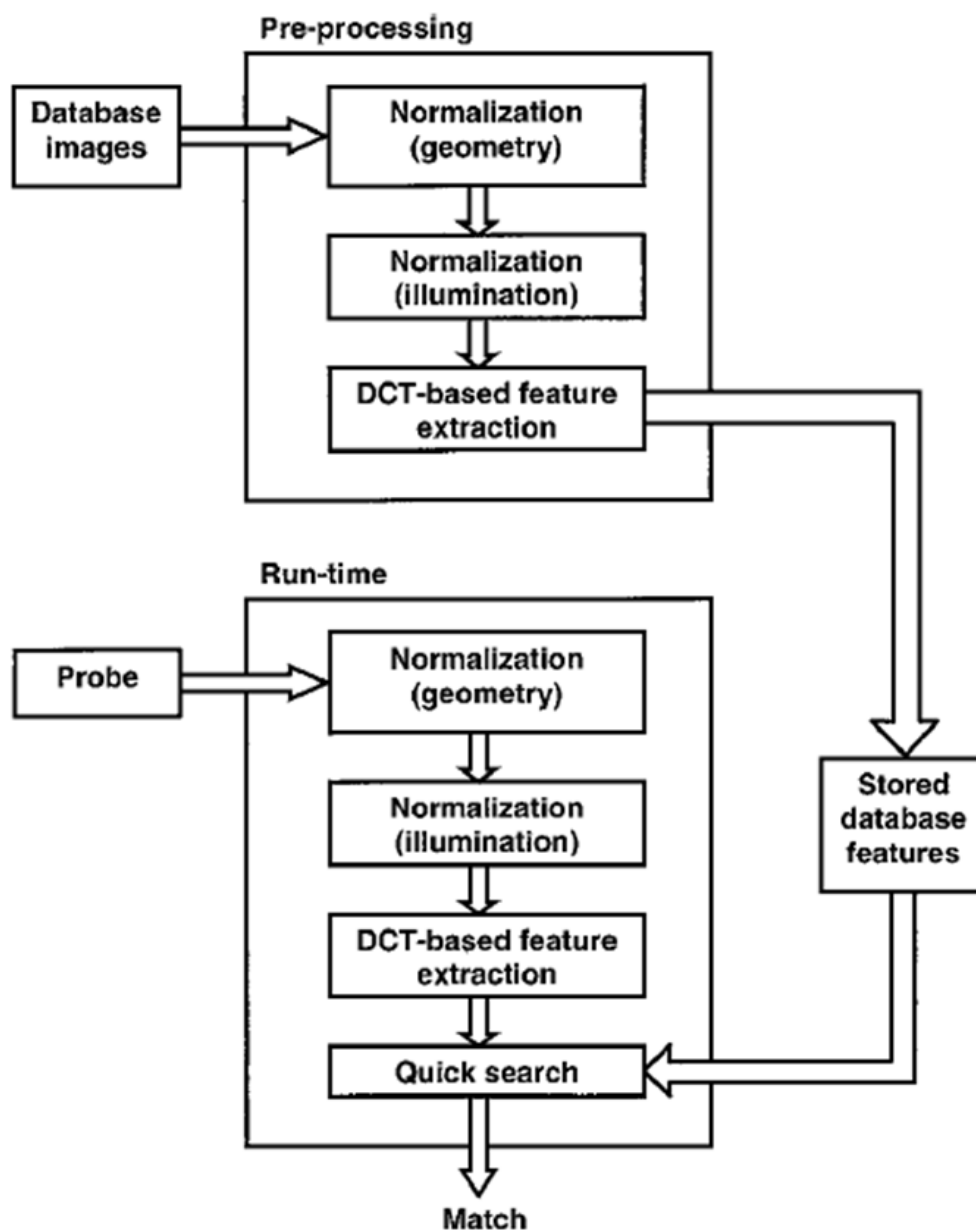


Figure 4: Flow Chart of Face Recognition Algorithm using DCT

same nominal size, position, orientation and illumination conditions. It is compared on the basis of features extracted from the DCT coefficients. Basically we have to compute the DCT of the face after normalization and keep a subset of DCT coefficients as the feature vectors which describes the face.

The feature vector contains all the low-to-mid frequency DCT coefficients, having the maximum variance. For recognizing a particular face which is given as input to the system, it compares the feature vector of the given face to the feature vectors of the images in the database using the Euclidean distance nearest-neighbour classifier. Taking the feature vector of the probe as v and that of the faces in the database as f , the Euclidean distance between the two can be written as

$$d = \sqrt{(f_0 - v_0)^2 + (f_1 - v_1)^2 + \dots + (f_{M-1} - v_{M-1})^2} \quad (1)$$

where

$$\begin{aligned} \mathbf{v} &= [v_0 \quad v_1 \quad \dots \quad v_{M-1}]^T \\ \mathbf{f} &= [f_0 \quad f_1 \quad \dots \quad f_{M-1}]^T \end{aligned} \quad (2)$$

and here M is the number of DCT coefficients taken as feature vectors of the face. The best match is found by minimizing the Euclidean Distance, d .

Chapter4

Implementation

4. IMPLIMENTATION

4.1 Eigen Faces Approach

4.1.1 Recognition Procedure

1. First the input face was converted into its eigen face components. Then the input image is compared with the average face of the training set images and their difference is multiplied with each eigenvector of the L matrix. All the values represented weights and

$$\omega_k = u_k^T (\Gamma - \Psi)$$

were saved on a vector Ω .

$$\Omega^T = [\omega_1, \omega_2, \dots, \omega_M]$$

2. Then the face class which provided the best description about the input image, was determined. This was done by minimizing Euclidean distance between them.

$$\varepsilon_k = \|\Omega - \Omega_k\|^2$$

3. The input image would belong to a class if ε_k was below an established threshold θ_ε .

Then the face image would be considered as a known face. If the difference was above a certain threshold, but below the second threshold, the image would be determined as an unknown face. If the input image was above both of the two thresholds, the image was determined as NOT a face.

4. If the image which we found was an unknown face, we would have to decide if we desire to add the image to the training set for our future recognitions. If yes, then all the steps from 1 through 7 would be repeated to incorporate this new image into database images.

4.1.2 Code Description

The Eigen Face Algorithm works in the following way. In this code, jpg images were used for testing. In the first step several pictures from the above database (figure 1) were selected. After loading the images and performing several calculations the mean image was found out. Then an image is asked for the input. This input image is projected onto the face space created by eigen vectors, and based on the difference between the eigen vectors a decision is

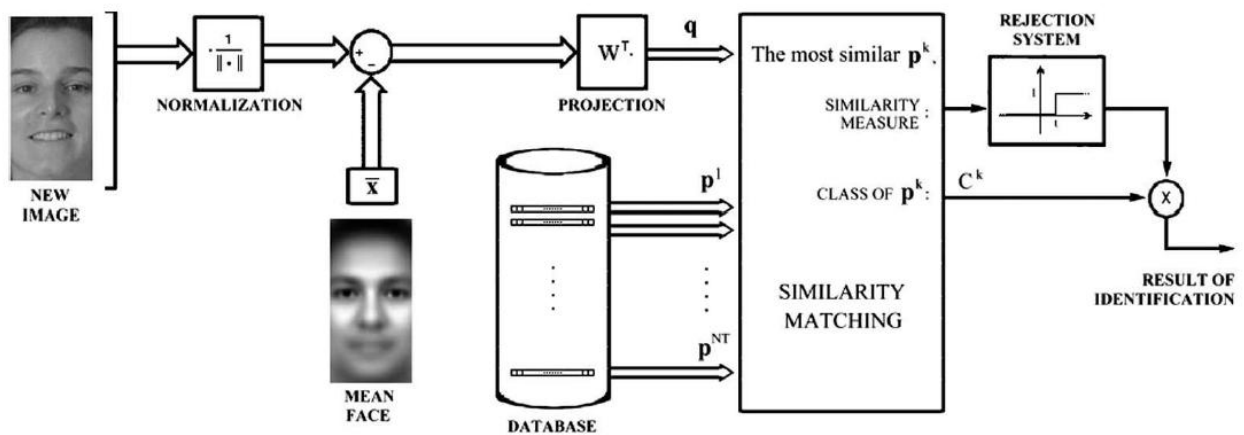


Figure 5: Flow Chart of Face Recognition algorithm using Eigen Faces

At first a known image present in the database of training set is taken as input and the Euclidean distance is calculated. The closeness and similarity between the given input image and the images present in the training set is given by the Euclidean Distance calculated in the previous step. From the figure it can be seen that the minimum distance is around 11000 maximum 15000. Then finally the decision is taken if this face is known or unknown, or not a face at all based on these distances.

4.2 DCT Approach

In this section, the DCT approach was put into test under a wide variety of conditions. Specifically, several databases, with many significant differences between them, were used in this experiment. The main purpose was to show the consistency of the results for a range of databases that had various constraints imposed on the face images acquired.

4.2.1 Face Databases Considered

4.2.1.1 The Achermann Database.

This database was acquired at the University of Bern in Switzerland which contained 300 images of 30 individuals. A set of 10 images was taken for each individual with certain constrained 3-D pose variations.

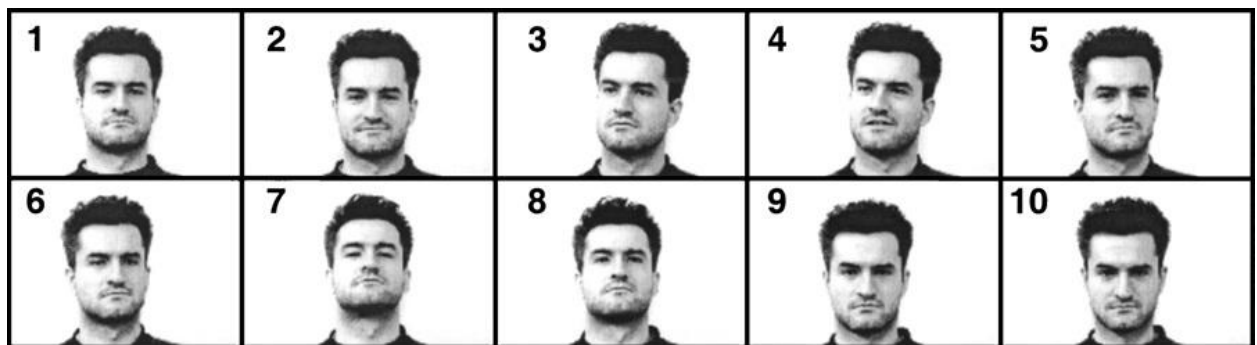


Figure 6: The Achermann Database

Figure 6 shows these variations for a typical face in the database. Note that background and lighting conditions were uniform for all images. Also this database permits the investigation of the sensitivity of the DCT to 3-D variations and the observation of the effects of increasing the number of training images per person on recognition accuracy. Finally, it should be mentioned that the database only contains males.

4.2.1.2. The Olivetti Database.

The Olivetti database, as the name itself suggests, originated from the Olivetti Research Laboratory in England. It consists of 400 images of 40 individuals. For each individual, ten images were taken and few constraints were imposed on facial expression and pose. Furthermore, some of the captured images were also subjected to illumination variations.

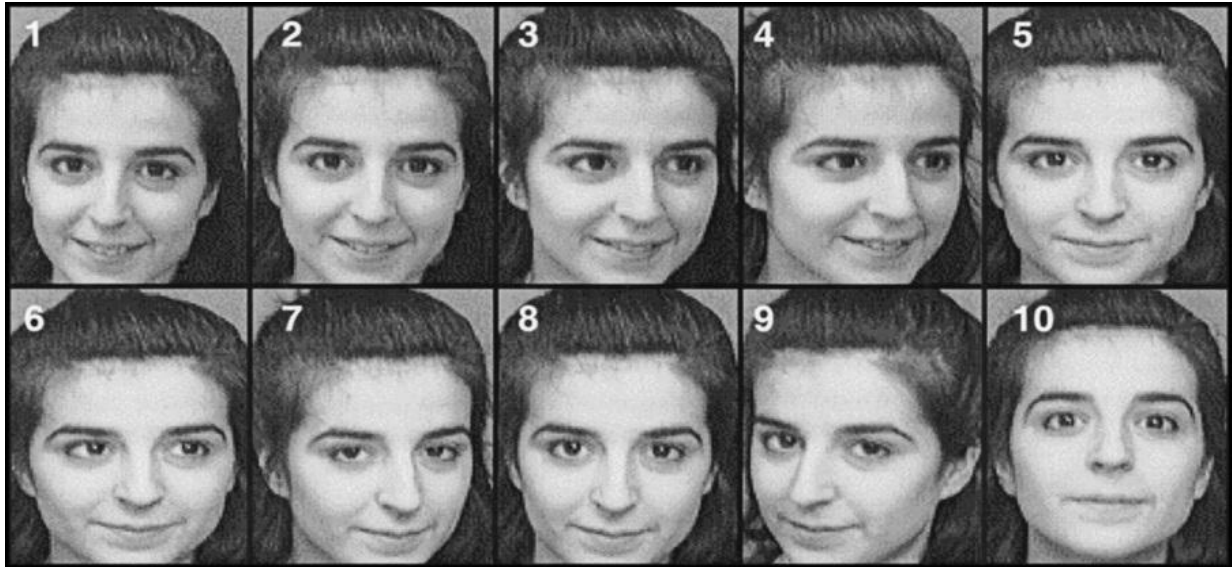


Figure 7: The Olivetti Database

However, the images do not include any backgrounds whatsoever. This database includes both males and females, and we can see the effects of an increased number of training images per person. Figure 7 presents a sample set from this database.

4.1.3. The MIT Database.

The MIT database used in this project consists of 432 images of 16 individuals. There were twenty-seven images for each person in the database and variations such as scale, orientation, and lighting were also included in this database.

Specifically, three cases of scale, three cases of lighting conditions, and three cases of orientation were considered. Then all possible combinations of these cases were taken. This database is mainly useful for testing the efficacy of both geometric and illumination normalization techniques described in the previous section. However, it is quite small and includes only males in the database.



Figure 8: The MIT Database

4.1.4. The CIM Database.

The final database considered in this project was the CIM Face Database, which was obtained at the Center for Intelligent Machines(CIM) in McGill University. It consists of 231 individuals and for this, 8 images per individual were taken. These 8 images covered variations in facial expression, 2-D orientation and 3-D pose, as can be seen from Fig.9. In fact, the CIM database combines the orientation variations of the MIT database with the 3-D pose variation of the Achermann database and the facial expression variations of the Olivetti database also.



Figure 9: The CIM database

It includes people of various age, gender, and skin tone and it thus poses a significant challenge to the DCT as well as to the normalization techniques used. An example of the variety of faces encountered in the CIM Face Database is shown in Figure 10. It should be noted that this database consists of approximately 70% males, 30% females, and 16% children.

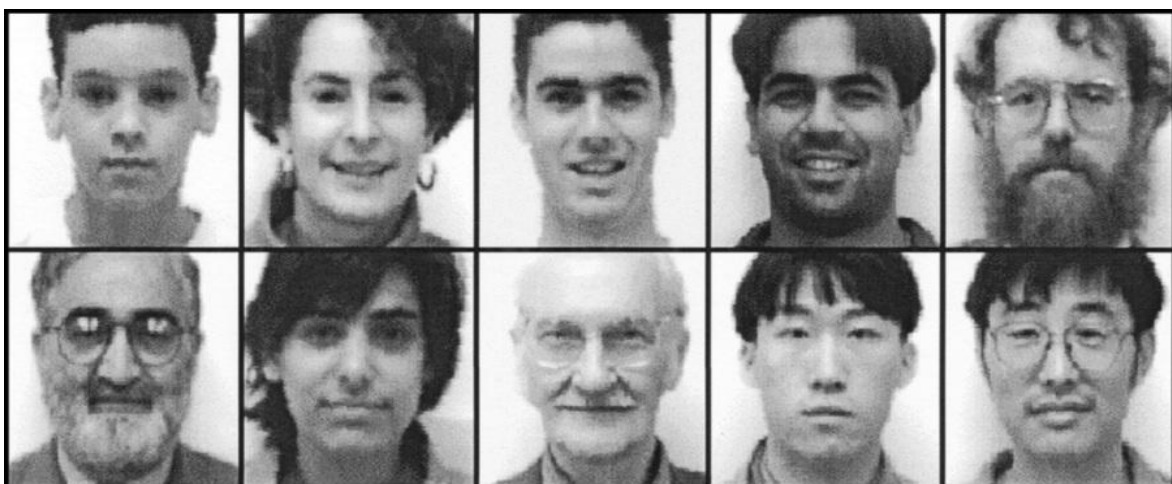


Figure 10: Database of people having various age, gender and skin tone

Chapter 5

Results

5. Result

5.1.Results of Eigen Faces Approach

5.1.1.

The first two images taken for the testing was from our training set. So it can be seen that the max and min Euclidean distance is within the specified range.

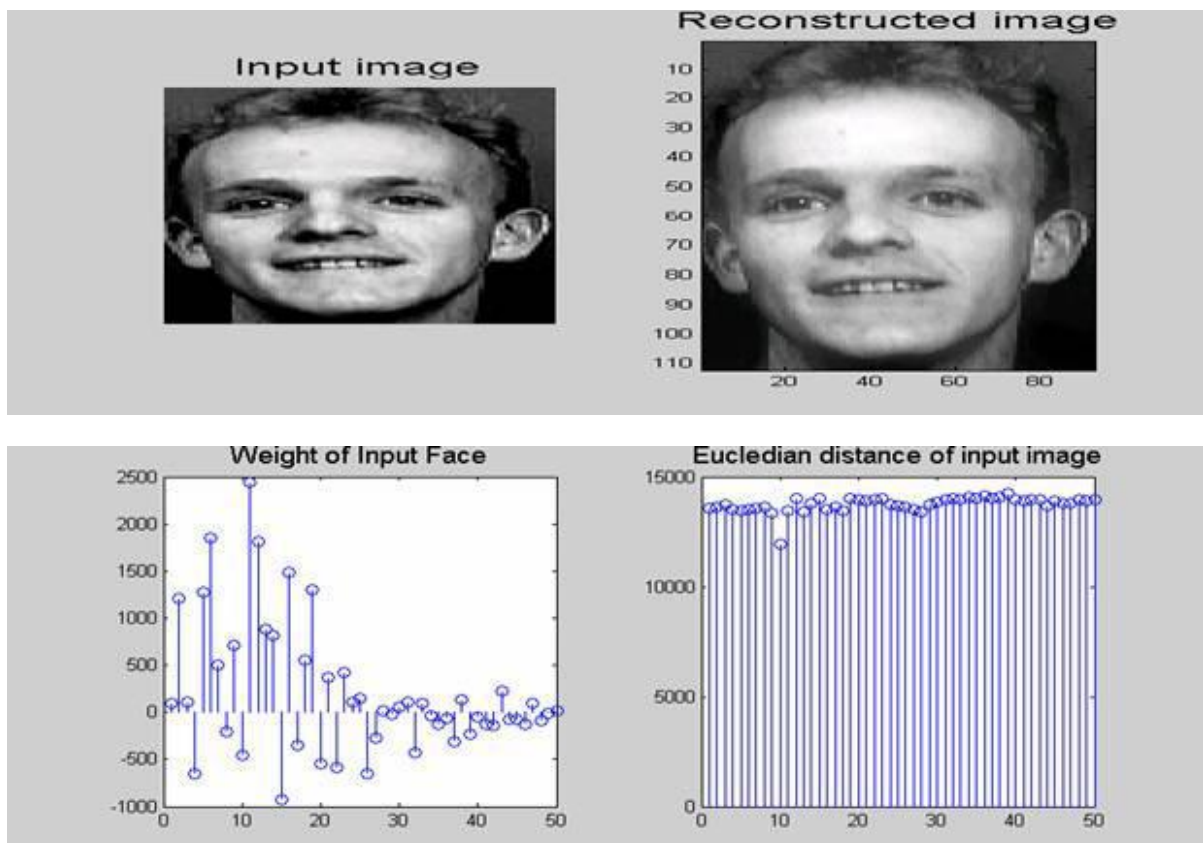


Figure 11: Result of Eigen face approach

Max Value :14266

Min Value : 11919

5.1.2. This is also an image from the training set.

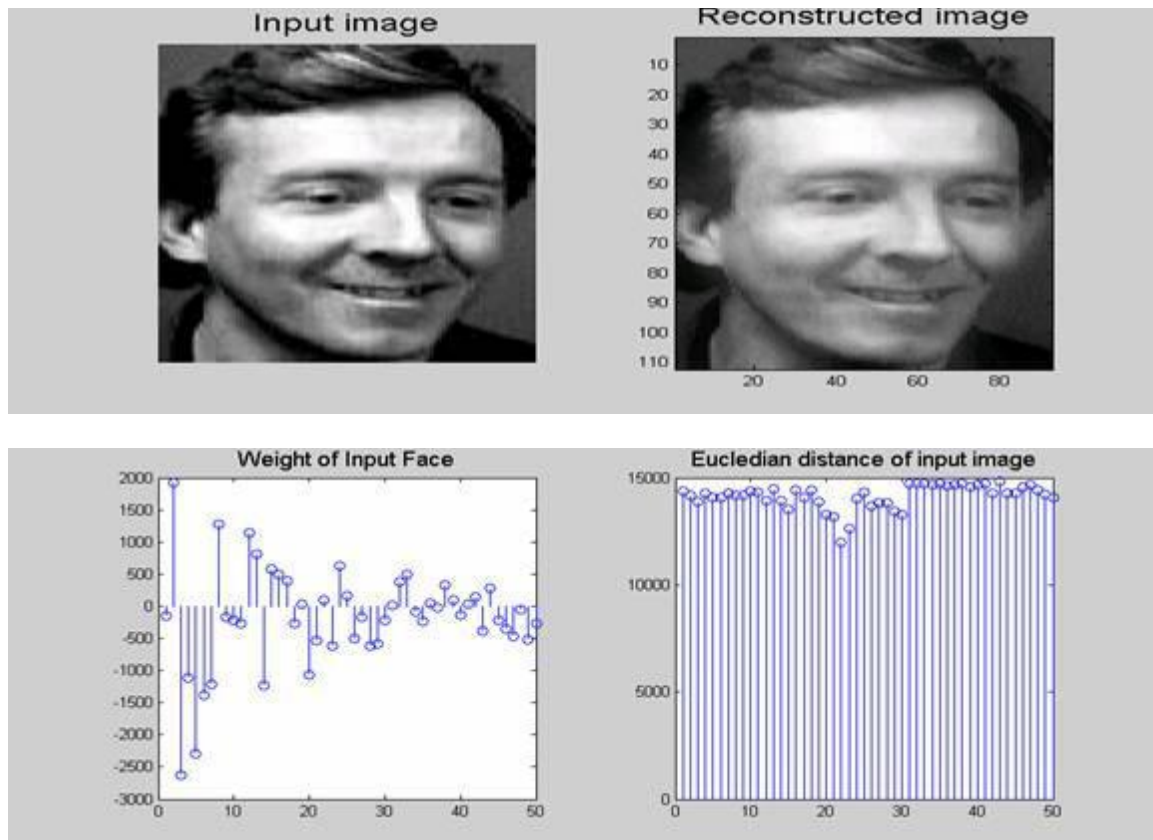


Figure 12: Result of Eigen face approach for a known face

Max Value: 14827

Min Value: 11960

5.1.3. After this an unknown face is taken for testing, and the results observed were different from the earlier result. The code could determine that the image was a face but could not recognise it. The max value was below the 15000 range. Thing which might look contradictory was that the maximum Euclidean distance for the unknown face was less than the distance obtained using a face from the training set. Moreover, the minimum value was higher as per expectation. Any decision to be taken is made on the basis of both on minimum and maximum distances.

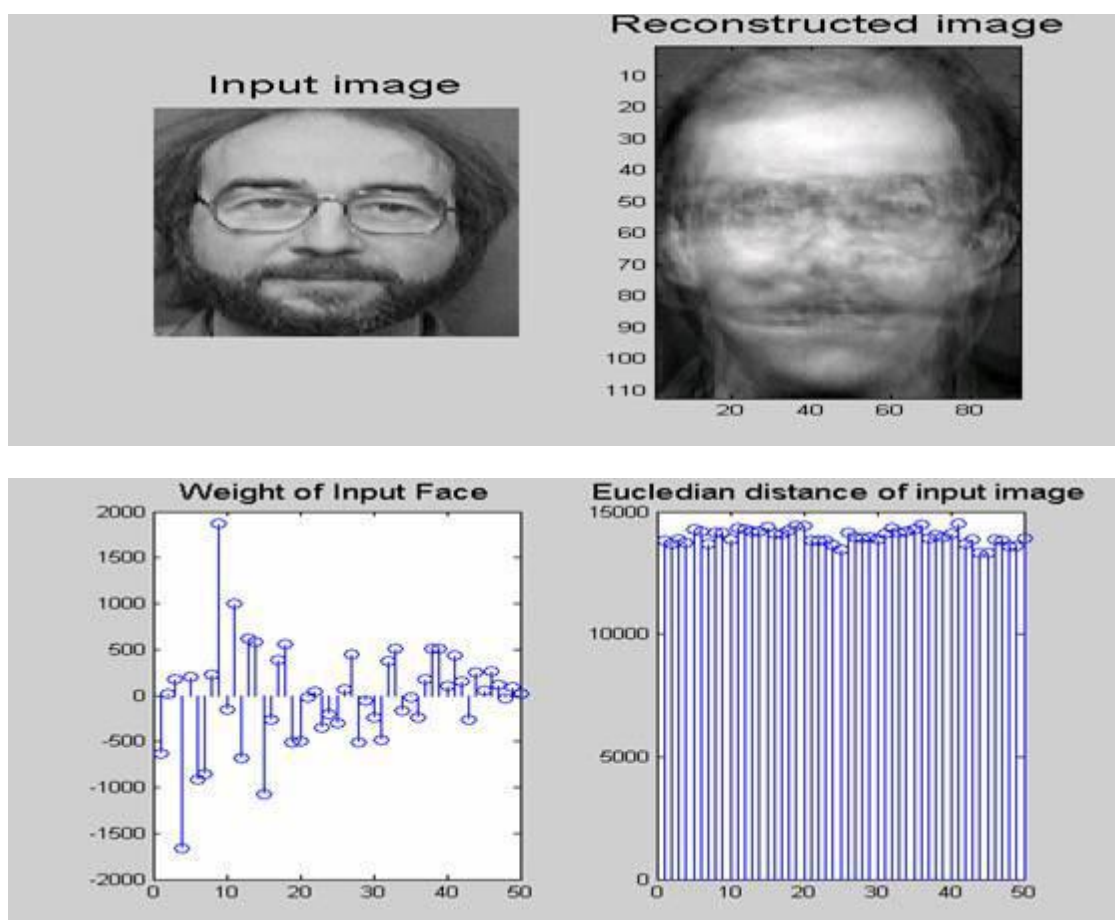


Figure 13: Result of Eigen face approach for an unknown face

Max Value : 14506

Min Value: 13321

5.1.4. After that images which were not faces, were used. In this case both the minimum and maximum values exceeded the 15000 limit. So the image was classified as not being a face.

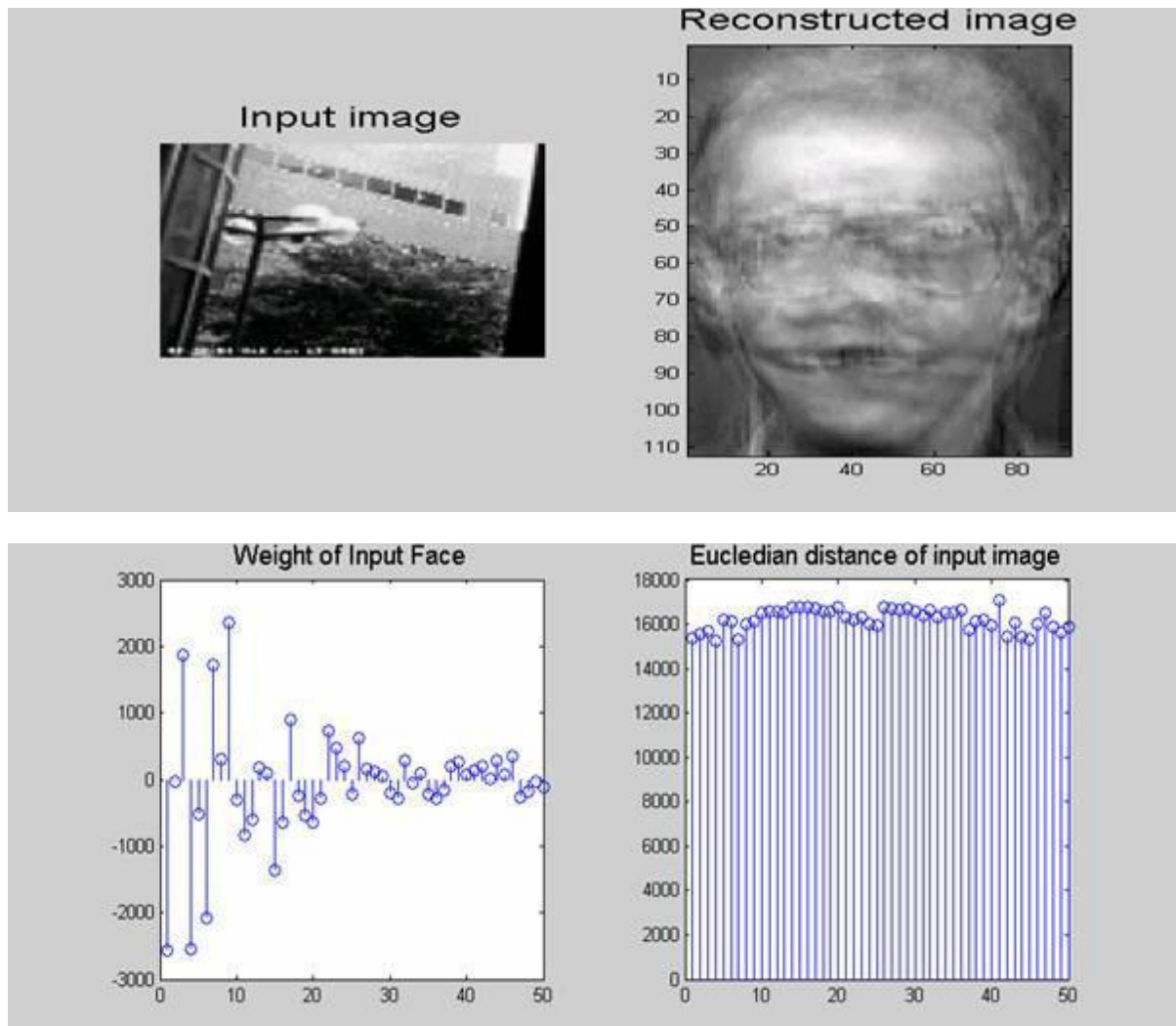


Figure 14: Result of Eigen face approach for an image, other than a face

Max Value: 17072

Min Value: 15260

5.1.5 In the last test, the face of an animal was used. It was seen that the minimum distance was within the 15000 range. The reason behind it is that animals have certain features which are similar to human face. The image was classified as not been a face because in our assumption a human face should be below the 1500.

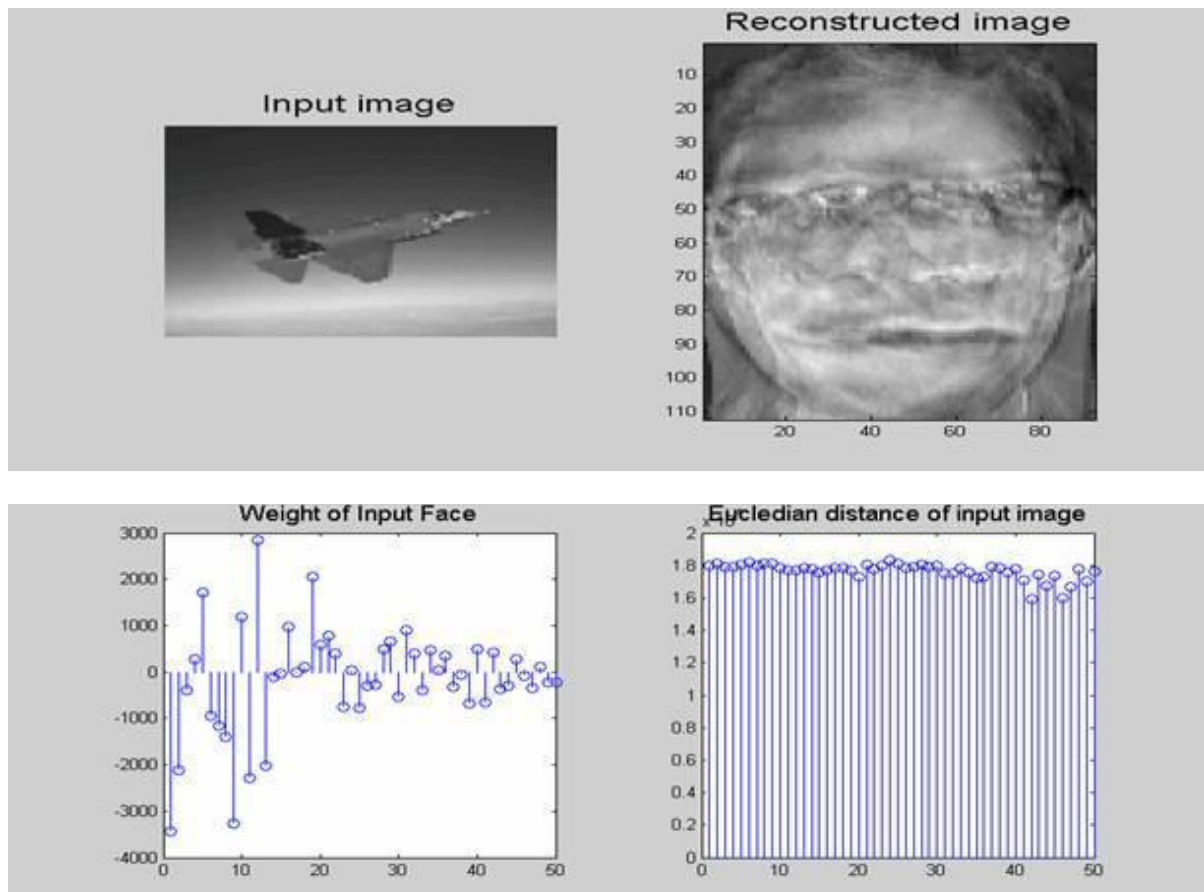


Figure 15: Result of Eigen face approach for an image, other than face

Max Value: 18323

Min Value: 15954

5.2. Result of DCT Approach

In this section, various results are presented and discussed. We begin with the effects of the number of training images per person on face recognition. Then the sizes of the various feature vectors is changed and its effects on recognition accuracy is observed. Next effect of normalization is tested and finally, some general results are presented.

5.2.1. Number of Face Models Per Person.

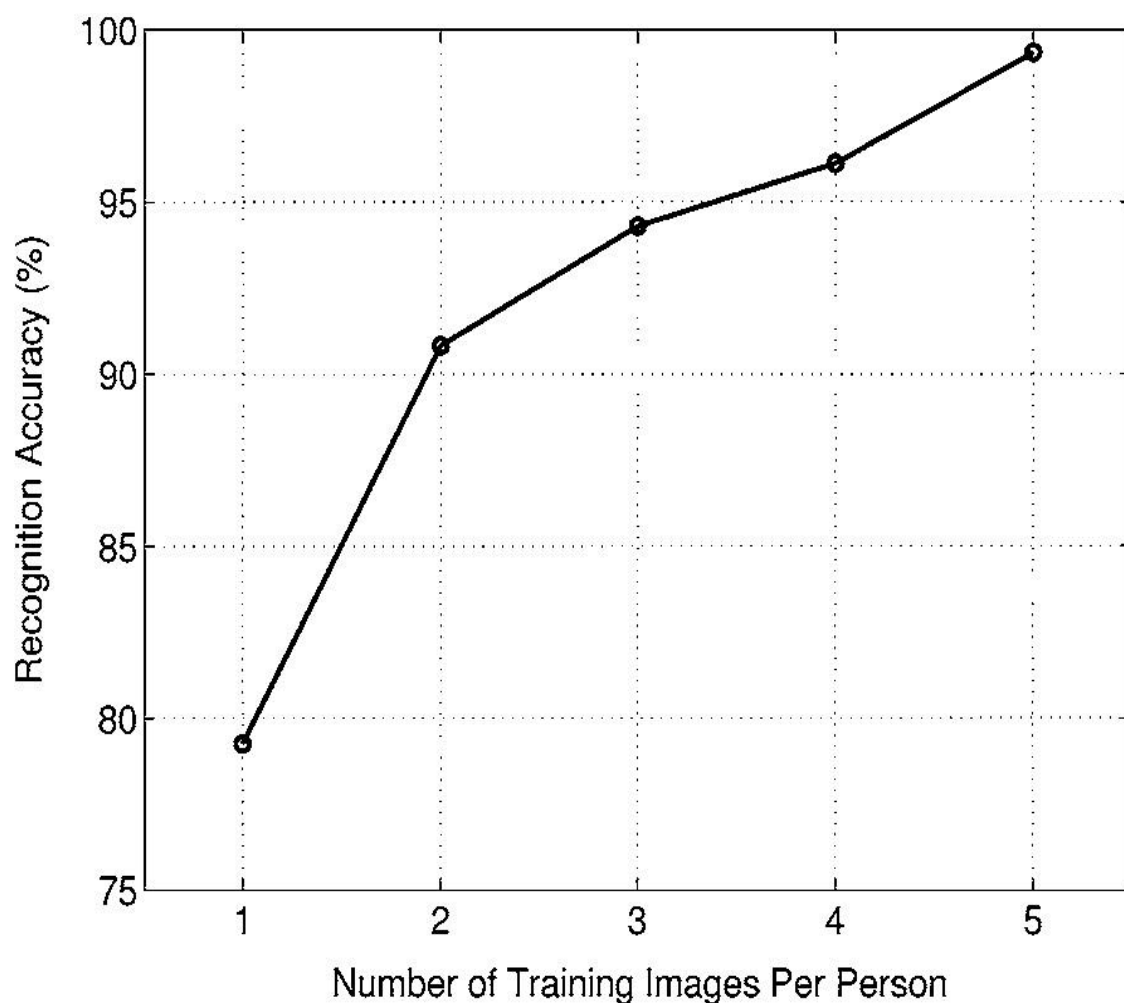


Figure 16: Recognition Accuracy vs No of Training Images per person

It can be seen that the recognition accuracy of a face recognition system increases with the increase in the number of face models per person.

5.2.2. Number of DCT Coefficients.

Here, the recognition accuracy of the system is presented as a function of the number of DCT coefficients used. It can be observed that the recognition accuracy becomes very high at certain points, where it actually exceeds 99%. Also it can be seen that there is a slight decrease in recognition accuracy as we go to higher numbers of coefficients.

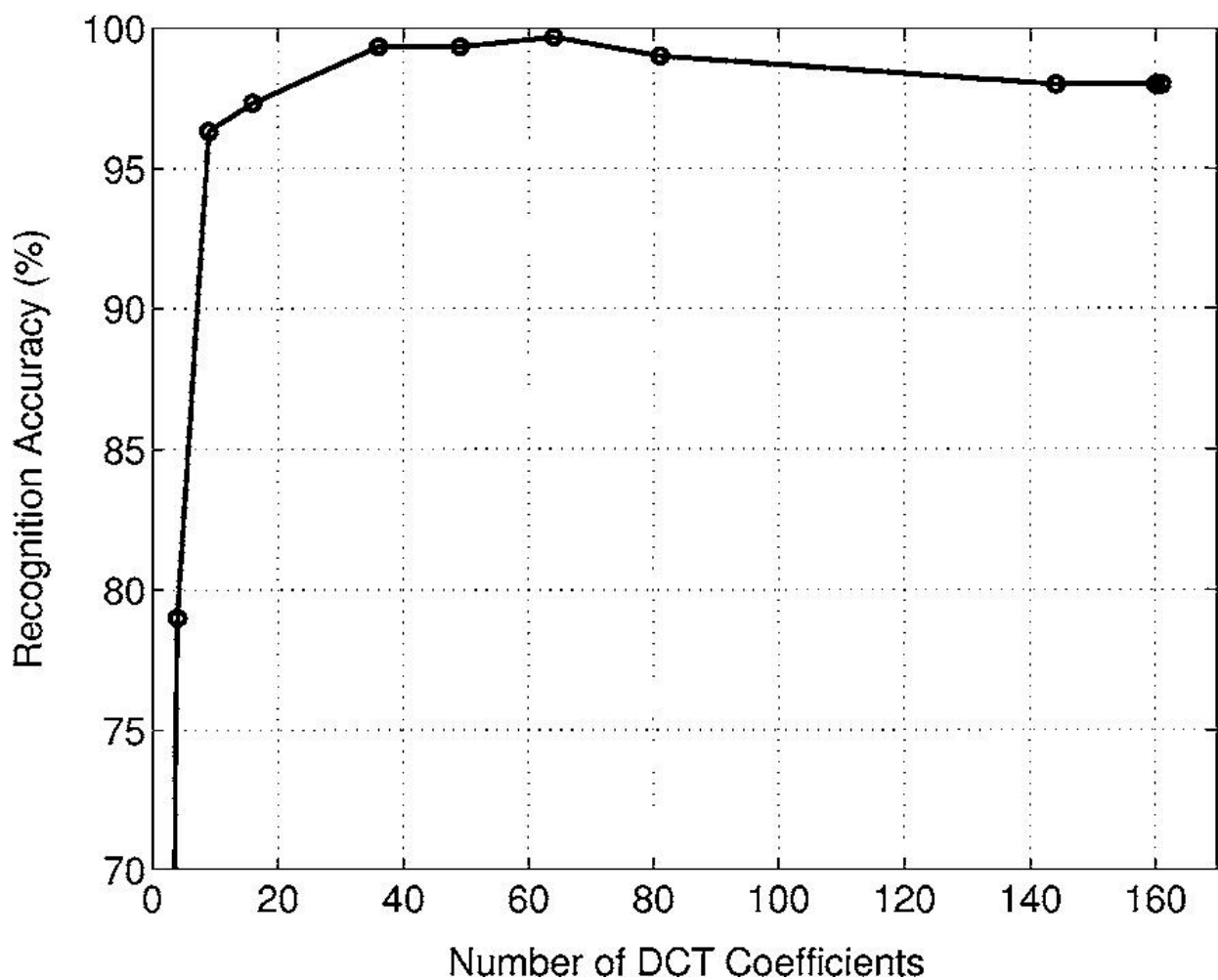


Figure17: Recognition Accuracy vs No of DCT Coefficient

5.2.3. Geometric Normalization

Orientation variation can have detrimental effect on our face recognition system. Here we can see that the system's recognition rate has been fairly improved with normalized face images.

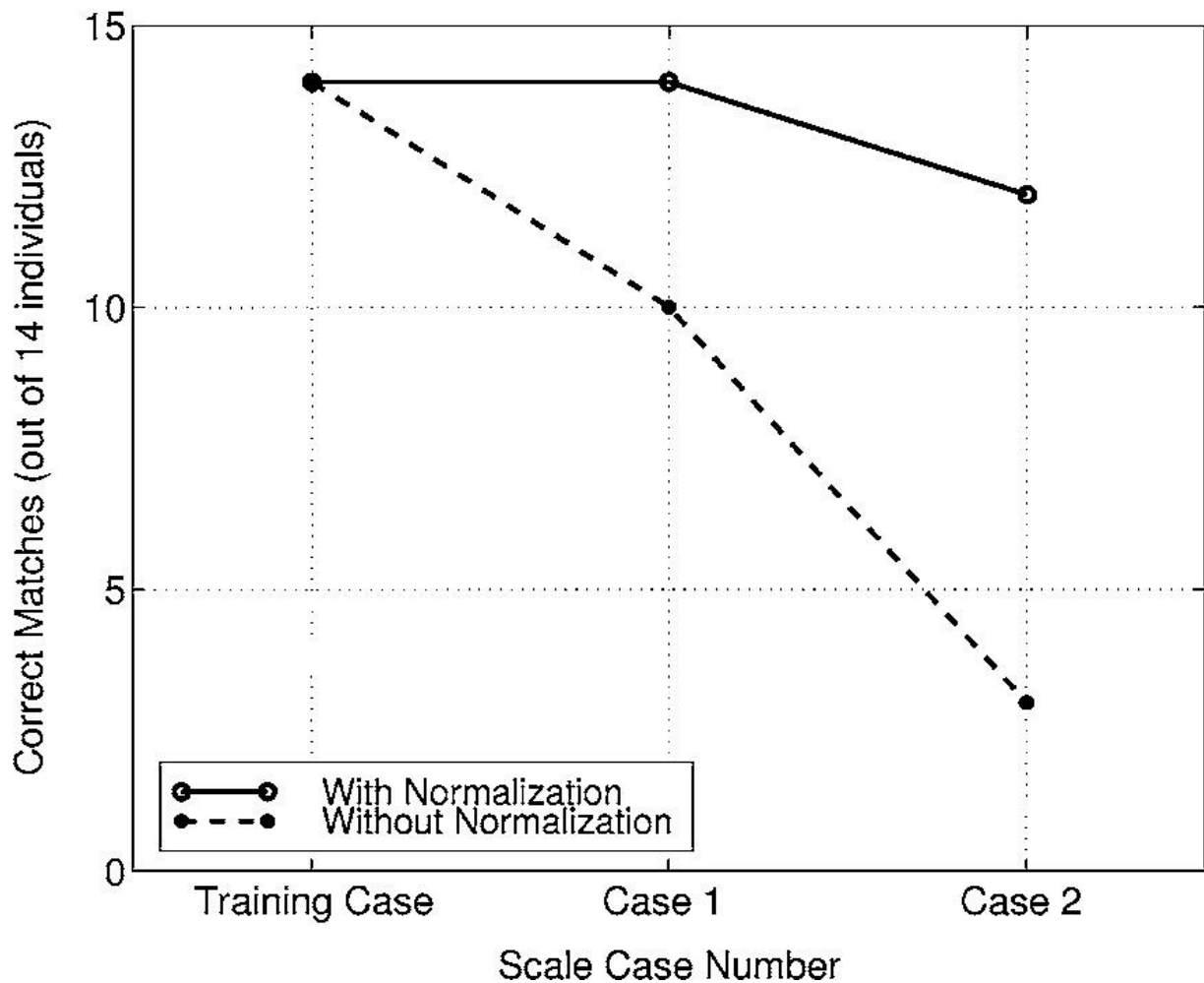


Figure 18: Recognition accuracy vs Normalized Faces

5.2.4 Cumulative Recognition Accuracy

The result presented below shows cumulative recognition accuracy as a function of rank for a variety of conditions. The basic idea behind this format is to show that even if the closest match (rank 1) may not be the correct match, the correct match almost always appears in the top, say, 50 matches (or ranks). That is, if cumulative recognition accuracy for a particular experiment is 90% at rank 20, then the correct match is among the closest 20 matches, 90% of the time. In this case, the CIM database is chosen because of its size and variety. As it can be observed, the results are as expected: there is an increase in the cumulative recognition accuracy with increase in the rank.

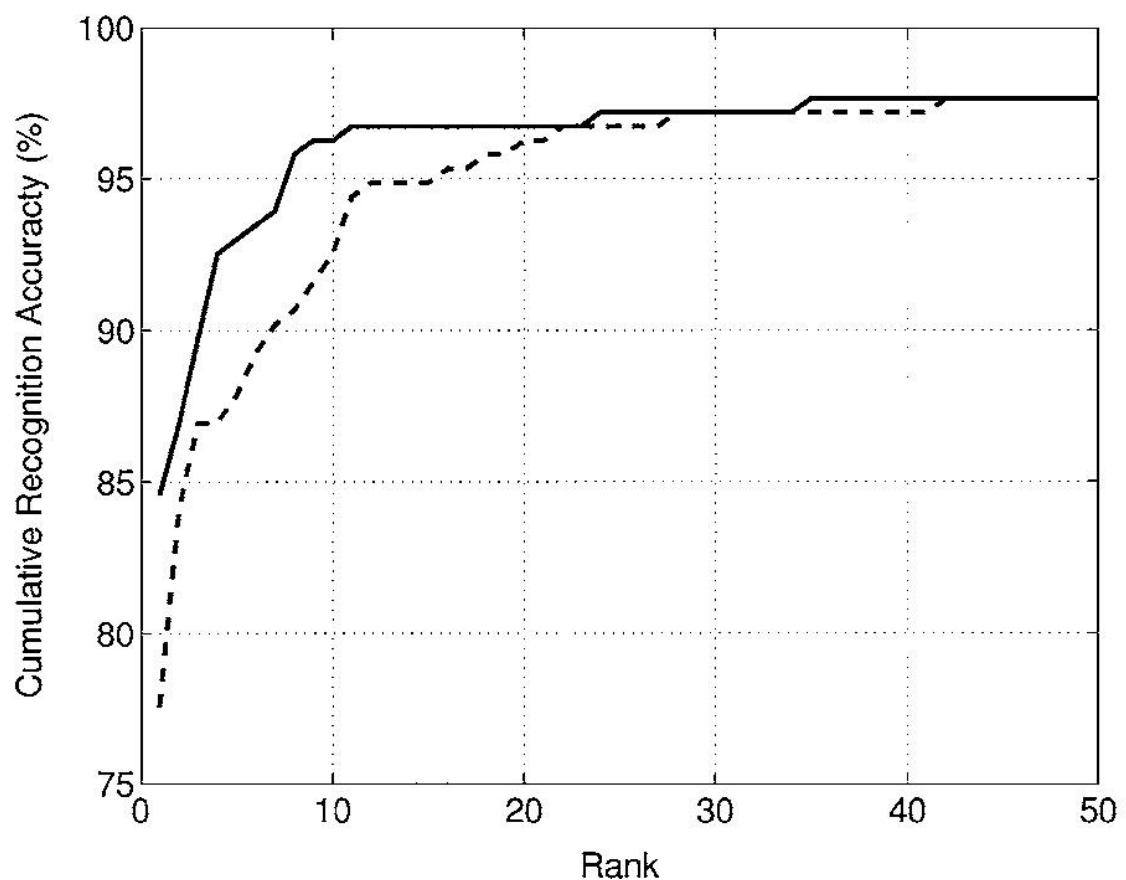


Figure 19: Cumulative Recognition Accuracy as a function of Rank for a variety of conditions

Chapter6

Conclusion

5. Conclusion

In this thesis Eigen Faces Approach and DCT based approach were used to implement the face recognition system. Eigen faces approach is robust in the treating face images with varied facial expressions and directions. This approach is very simple and efficient for both training and recognition stages, requiring low level of processing for verifying the facial geometry or the distances between facial dimensions and their geometry. However, this approach has certain drawbacks which are required to be overcome in order to increase the efficiency and correctness of face recognition process. It suffers from Illumination (with changes in light condition the performance degrades), Image Background (outside of the face is deemphasized), Head Orientation (performance decreases because of change in head orientation) and Scale (with change in the head size performance decreases abruptly). Further, presence of small facial details such as moustache, masks or dark glasses also creates problem for the system.

DCT approach overcomes all the above listed drawbacks in Eigen Face Method. As a result, the results of DCT approach are quite satisfactory, but still face localization capabilities are lacking in this system. Template matching algorithms are implemented for finding faces or eyes in images by using frequency domain information obtained from the DCT approach. This helps to make this algorithm completely independent of the manual input of eye coordinates. 3D Pose variation like change in head orientation can be accounted for by using geometric normalization. It was observed that dark coloured faces were brightened up and light coloured faces were artificially tainted due to the choice of target face illumination applied during Histogram Modification. Thus, skin color can be used to categorize individuals by defining different target illuminations, which is independently tuned to suit different subsets of the population. This classification approach can have the advantage of decreasing the sensitivity of the recognition system to illumination normalization.

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